Bringing space into the equation: Modelling the social and spatial interdependence of neighborhood effects on educational outcomes

Zangger, Christoph

Abstract: While there is an ever-growing body of research on neighborhood effects on various forms of life chances, the suggested social mechanisms still refer to rather ambiguous theoretical concepts. Furthermore, previous research seldom adequately models the suggested social interdependence at the individual level. Instead, researchers largely rely on contextual regression models. This paper addresses both problems by using spatial econometrics to reconstruct neighborhood effects in terms of interdependent social action. To this end, a rational action model of neighborhood effects on educational outcomes is elaborated as a theoretical alternative. Furthermore, using data on the transition to secondary school in Switzerland as an illustration, spatial probit models are estimated to directly test neighborhood effects at the individual level. It can be shown how the interdependence of parental educational motivation within neighborhoods crucially shapes students' transition to the more advantageous school track, thereby revealing an additional path by which educational inequalities are reproduced.

DOI: https://doi.org/10.1016/j.rssm.2018.03.007

Originally published at:
Zangger, Christoph (2018). Bringing space into the equation: Modelling the social and spatial interdependence of neighborhood effects on educational outcomes. Research in Social Stratification and Mobility, 55:63-74.
DOI: https://doi.org/10.1016/j.rssm.2018.03.007

ABSTRACT

While there is an ever-growing body of research on neighborhood effects on various forms of life chances, the suggested social mechanisms still refer to rather ambiguous theoretical concepts. Furthermore, previous research seldom adequately models the suggested social interdependence at the individual level. Instead, researchers largely rely on contextual regression models. This paper addresses both problems by using spatial econometrics to reconstruct neighborhood effects in terms of interdependent social action. To this end, a rational action model of neighborhood effects on educational outcomes is elaborated as a theoretical alternative. Furthermore, using data on the transition to secondary school in Switzerland as an illustration, spatial probit models are estimated to directly test neighborhood effects at the individual level. It can be shown how the interdependence of parental educational motivation within neighborhoods crucially shapes students' transition to the more advantageous school track, thereby revealing an additional path by which educational inequalities are reproduced.

Keywords: Neighborhood Effects, Educational Attainment, Rational Choice, Spatial Econometrics, Social Multipliers

Bringing Space into the Equation: Modelling the Social and Spatial Interdependence of Neighborhood Effects on Educational Outcomes

1. Introduction

While an ever increasing body of research suggests that individual life chances in general (e.g., Morenoff, Sampson, & Raudenbush, 2001; Oakes, Andrade, Biyoow, & Cowan, 2015) and educational attainment in particular are crucially shaped by the contexts in which people live (e.g., their neighborhood, city or region: Ainsworth, 2002; Brännström, 2008; Crane, 1991; Garner & Raudenbush, 1991), the social mechanisms explaining such contextual and compositional effects are usually formulated rather vaguely. Instead, researchers often refer to broad theoretical concepts such as collective socialization or the epidemic spread of norms (Galster, 2012; Sampson, Morenoff, & Gannon-Rowley, 2002). Furthermore, the identification of neighborhood effects is impeded by several methodological challenges. These include the proper assessment of the scale of "neighborhood", the separation from other contextual influences (e.g., school effects), unobserved selection processes, or the identification of endogenous effects (Durlauf, 2004; Lupton & Kneale, 2012; Manski, 1993; Oakes, 2004; Sykes & Musterd, 2011). Although researchers are increasingly aware of these issues, another aspect has largely been neglected. While most theoretical approaches to neighborhood effects imply a certain social and spatial interdependence of observational units, the methods used to test these models largely rely on the assumption of independent observations and fail to incorporate any spillover from one unit to another (LeSage & Pace, 2009). Thus, apart from the necessity of elaborating the mediating social mechanisms of neighborhood effects in more detail (Sharkey & Faber, 2014; Wodtke, Elwert, & Harding, 2016), we need to endeavor to match the theoretical and the empirical framework.

The aim of the present contribution is to address both the theoretical as well as the methodological problems. On the one hand, a theoretical model based on interdependent social action is elaborated as a theoretical alternative. To this end, the well-established educational decision-making framework (Boudon, 1974; Breen & Goldthorpe, 1997; Erikson & Jonsson, 1996) is extended by introducing social and spatial dependence among rational actors and their subjective expectations of the costs and benefits of the different alternatives. It is then evaluated to what extent introducing space into the original Breen-Goldthorpe model offers an explanation for the documented neighborhood effects on educational outcomes. This approach enables the direct testing of a particular mechanism through which neighborhoods can be expected to influence educational attainment.

On the other hand, an alternative empirical framework to assess the proposed neighborhood effect at the individual level is introduced. In this regard, the social interdependence of people's actions in a given context, such as the neighborhood in which they live, requires a methodological framework that abandons the assumption of identical and independently distributed observations (Cressie, 2015; LeSage & Pace, 2009). To this end, spatial econometric techniques are used to reconstruct the mutual dependence of people and their choices within the neighborhood context. By doing so, it can be shown how educational decisions and careers are not only the result of individual reasoning but also the choices and actions of others within the neighborhood. More generally, the theoretical and notably the methodological frameworks represent a toolkit for a better understanding and modelling of contextual effects and aligned decision making in social research. Finally, understanding the effects of intertwined educational choices in different contexts also bears potential with regard to formulating more adequate policies for reducing educational inequalities (Galster, 2002, 2012; Lupton & Kintrea, 2011).

Making use of the multiplying effects of social interdependencies and taking context into account, such policies can promote educational equality beyond the effect of programs that target single individuals.

The remainder of this paper is organized as follows. In the next section, existing research on neighborhood effects is briefly summarized. In the third section, an alternative model of spatial and social interdependence in educational decision making is elaborated. Additional information about the Swiss education system is provided in the fourth section. The data and the methodology are introduced in the fifth section, while the sixth section presents the results. The last section concludes with a critical discussion of the presented evidence and its relevance for explaining persistent social inequalities in education. Furthermore, it discusses the potential value of the presented methodological strategy for sociological research in general.

2. Neighborhood Effects on Educational Outcomes: Assessing the Evidence

Building on Wilson's (1987) seminal work of the epidemic spread of norms and behavior in areas of concentrated poverty, scholars have reported negative effects of deprived neighborhoods on various types of educational outcomes in children (e.g., Andersson & Malmberg, 2015; Crane, 1991; Garner & Raudenbush, 1991; Harding, 2003; Leventhal & Brooks-Gunn, 2000). Moreover, research concerned with the theory of collective socialization, focusing on the influence of local social networks, peers, and high status neighbors as role models, has found positive impacts of advantaged neighborhood environments on children's and adolescents' educational achievement and attainment (Ainsworth, 2002; Andersson & Subramanian, 2006; Brännström, 2008; Goux & Maurin, 2007; Kauppinen, 2007; Rosenbaum, 1995; Wodtke et al., 2016). However, the suggested mechanisms (i.e., the epidemic spread of norms or forms of social learning from others within the neighborhood) are usually assessed indirectly using aggregated measures, such as the share of high or low-income residents within the neighborhood.

Furthermore, results differ greatly by the methodological frameworks used and are dependent on the wider (urban and national) context. While studies using (quasi-)experimental data usually find weak effects, or even no effects (e.g., Kling, Liebman, & Katz, 2007; Ludwig et al., 2008; Rosenbaum, 1995), research using survey data reports persistent and sometimes strong evidence for neighborhood effects on educational outcomes (e.g., Ainsworth, 2002; Goux & Maurin, 2007; Leventhal &

Brooks-Gunn, 2000; Sharkey & Faber, 2014). Although this discrepancy partly reflects the difficulties of conducting large scale, long-term social experiments (Clampet-Lundquist & Massey, 2008; Sampson, 2008), it especially demonstrates the methodological problems faced when researching contextual and compositional effects (Durlauf, 2004; Manski, 1993). However, given that levels of segregation and welfare policies differ considerably between countries and namely between Europe and United States (Musterd, 2005), neighborhood effects are often less pronounced or even absent in the European context (Andersson & Malmberg, 2015; Kauppinen, 2008; Zangger, 2015).

Similarly, existing evidence also shows that the effects of neighborhoods on educational outcomes are heterogeneous across individual social background, gender, and developmental period (e.g., Andersson & Malmberg, 2015; Chetty, Hendren, & Katz, 2016; Sharkey & Faber, 2014; Wodtke et al., 2016; Zangger, 2015). Thus, the exposure to a common neighborhood can be associated with distinct outcomes for different social groups. In the following, we will therefore take a closer look at how such neighborhood effects in the particular case of educational attainment might be explained in terms of individual choices and the interaction with others.

3. From the Ground up: Putting Individual Decision Making into Context

Although neighborhood effects do make a difference for children's educational attainment, they have often been neglected in explanations for persistent inequality in education. Instead, scholars have proposed different theoretical frameworks for explaining educational inequalities spanning from the role of individual aspirations (e.g., Duncan, Haller, & Portes, 1968; Page, Levy Garboua, & Montmarquette, 2007; Sewell, Haller, & Portes, 1969) to compositional effects in different types of schools (e.g., Coleman, Hoffer, & Kilgore, 1982; Morgan, 2001). However, when it comes to explaining persistent social inequalities in education (Becker, 2003; Breen & Jonsson, 2005; Breen, Luijkx, Muller, & Pollak, 2010), one particular model of educational decision-making has received special attention in the literature. Building on Boudon's (1974) distinction of primary and secondary effects of social origin, Breen and Goldthorpe (1997) developed a theory of educational inequalities in terms of a rational action framework. Ever since, scholars have refined and extensively tested the validity of this framework (e.g., Breen & Jonsson, 2005; Stocké, 2007).

However, the Breen-Goldthorpe model as well as its extensions assume that the evaluation of the explanatory parameters (e.g., the costs and benefits) is a purely individual cognitive and motivational process. This view of independent actors, however, is challenged by the above reported evidence on both neighborhood and peer effects in other contexts, such as classrooms and schools (Hanushek, Kain, Markman, & Rivkin, 2003; Sacerdote, 2011). Thus, the question is, how to incorporate this interdependence into a model of individual action and if in turn this interdependence explains the documented neighborhood effects.

To this end, let us first consider a generalized version of the original model, as depicted in equation (1). An alternative k is chosen if its utility U_k exceeds that of all other alternatives U_l. Furthermore, $\pi_{k,l}, p_{k,l} \in (0,1)$ denote the probability of success and the propensity of status decline, respectively. $-SD$ reflects the importance of status maintenance, $C_{k,l}$ the costs, and $B_{k,l}$ the subjective expected benefits for alternatives k and l. While $\pi_{k,l}$, $C_{k,l}$, $p_{k,l}$, and (as a consequence) $U_{k,l}$ in equation (1) differ with individual social origin (Breen & Goldthorpe, 1997), we can think of two—at first sight seemingly contradictory—paths through which interdependence could be introduced into the original educational decision-making model.

$$U_k = \pi_k B_k + [(1-\pi_k)p_k(-SD) - C_k] > \pi_l B_l + [(1-\pi_l)p_l(-SD) - C_l] = U_l \qquad (1)$$

Following the overall assumption, individual i is confronted with the decision on entering a higher educational track k versus a lower one l. Either of the two tracks is associated with different educational credentials and, therewith, likelihoods of gaining distinct social positions. In return, the implied hierarchy of different social positions (Breen and Goldthorpe's (1997) 'societal consensus') shapes people's aspirations for different educational alternatives. However, such aspirations are not directly included in the above outlined model. In a rational action framework, we can think of aspirations A_{ik}, A_{il} as an individual i's motivation for the alternatives k and l. As others have pointed out (Becker, 2003; Esser, 1999; Stocké, 2007), the individual educational motivation for alternatives k and l is given as the sum of the subjectively expected benefits and their instrumentality for status maintenance:

$$A_k = B_k + p_k \times (-SD) \quad \text{and} \quad B_l + p_l \times (-SD) = A_l. \qquad (2)$$

Furthermore, such aspirations, and their role in the reproduction of educational inequalities, have been demonstrated to be interdependent within a given context (e.g., a classroom or a network of peers (Carbonaro, 1998; Coleman, 1988; Duncan et al., 1968; Lupton & Kintrea, 2011; MacLeod, 2011; Roth, 2017; Sewell & Armer, 1966; Sewell et al., 1969). Hence, the empirically documented interdependence of aspirations, translated into a rational action framework (framed as people's educational motivations), can be expected to work through one or several of the parameters $B_{k,l}$, $p_{k,l}$, or $-SD$. More specifically, we can assume an effect of the aforementioned societal consensus regarding a hierarchical order of class positions on the subjectively expected risk of status decline $p_{k,l}$. Given individual social status, one's beliefs about the risk of status decline as a consequence of the pursuit of alternatives k or l are partially shaped by interactions with others. In these interactions, people obtain information about others' assessments of $p_{k,l}$, which, in turn, contributes to the formation of the societal consensus (the social status S_{D1} of, for example, a medical doctor exceeds the social status of S_{D2}, e.g., a teacher, if people regard S_{D1} but not S_{D2} as sufficient for maintaining their social status). A similar argument can be made in the case of the benefits $B_{k,l}$. Although the individual assessments of the benefits of alternative k or l are assumed to be constant within a given social stratum (Becker, 2003), the exchange with others might effect a change in the evaluation of the benefits, especially in the case of cross-cutting social ties (Burt, 2000; MacLeod, 2011). In their interaction with members of the upper class, parents of lower social classes might obtain new information about the value of further education or the workings of the education system. Finally, the importance people attribute to maintaining their social status ($-SD$) is most likely constitutes an individual assessment, shifted by individual social status. Although the societal context clearly structures in how far a decline in social status must be considered a "loss," it seems rather unlikely that the interaction with others directly changes one's expectation of a potential status decline, other than through $p_{k,l}$. Allowing for significant others' influences in the Breen-Goldthorpe model (in the present context: of other parents in the neighborhood), we can rewrite i's educational motivation for the higher track k and the lower track l as the sum of the individual educational motivation (A_{ik} and A_{il}) and a weighted influence of his or her neighbors' motivation for the same alternatives (A_{jk} and A_{jl}):

$$A_i\left[k|A_j(k)\right] = A_{ik} + \theta_{jk} w_{ij} \underbrace{\left[B_{jk} + \left(p_{jk} \times -SD_j\right)\right]}_{A_{jk}}$$

and

(3)

$$A_i\left[l|A_j(l)\right] = A_{il} + \theta_{jl} w_{ij} \underbrace{\left[B_{jl} + \left(p_{jl} \times -SD_j\right)\right]}_{A_{jl}},$$

In equation (3), w_{ij} is an element of a binary contiguity matrix $\boldsymbol{W}$, indicating whether two observations, i and j, are “neighbors” and a weight $\theta_{jk,l}$. Equation (3) thus allows for the subjective expected utility of the two tracks k and l to depend upon others’ educational motivation for the same alternatives. In addition, the likelihood $\pi_{k,l}$ of successfully completing alternatives k and l is assumed to be interdependent due to the same arguments just made for $p_{k,l}$. Although one can imagine that the subjective evaluation of the costs might also change as a function of additional information provided by others (for example by correcting for a lower class parents’ overestimation of the costs (Becker, 2003)), the effective, measurable costs, $C_{k,l}$, are assumed to be fixed (Paulus & Blossfeld, 2007). On the other hand, we cannot rule out the possibility that especially the assessment of the opportunity costs of (not) following either the lower or the higher track changes as a function of the interaction with others (Stocké, 2007). Nevertheless, the individual assessment of the direct monetary costs is not expected to change with others’ expectations. When it comes to the investment risk $C_{k,l}/\pi_{k,l}$ (Becker, 2003), we would therefore expect interdependence—if there is any—to work through the success probability $\pi_{k,l}$.

Table 1 about here

Focusing on the assumed direction of the interdependence, however, a second assumption about the explanatory mechanisms can be made. Although we would expect a positive correlation between two interdependent observations, i and j, with regard to their expectations of $B_{k,l}$, $\pi_{k,l}$, and $p_{k,l}$, the very nature of a stratified educational system also suggests negative effects in terms of the likelihood of attending the higher, more advantageous, track. Imagine a neighborhood of N elementary students whose parents are all motivated to send their children to the higher track k, that is, $B_{i,k} + p_{i,k} \times (-SD_i) > B_{i,l} + p_{i,l} \times (-SD_i)\ \forall\, i \in \{1, \ldots, N\}$. Further, assume that, due to limited places, only half of the students will be able to attend the higher track. As previous research has shown (e.g., Becker, 2003; Stocké, 2007), higher educational motivation for track k increases the propensity to attend it—independently of a student's performance. Hence, a particular student's probability of attendance can be expected to be lower if he or she is confronted with highly motivated peers and their parents.

Summing up, the interaction and exchange with other's likely changes people's evaluation of different educational alternatives. We therefore expect a positive interdependence of the outlined theoretical parameters in the neighborhood context. More specifically, the higher one's neighbors evaluate the benefits $B_{k,l}$, the likelihood of success $\pi_{k,l}$, and the instrumentality $p_{k,l}$, the higher one's own rating of the same parameters for the two tracks k and l (Hypothesis 1). On the other hand, the restriction of a more or less fixed number of places is likely to provoke negative effects in the case of the higher track k since, for example, it takes time to recruit additional teachers to deal with the higher demand for the more advantageous track. Consequently, highly motivated neighbors are expected to decrease the likelihood of one's own child attending the higher track (Hypothesis 2). Before we turn to the methodological strategy and the empirical evaluation of the hypotheses, additional information on the Swiss education system is provided briefly.

4. Transitions in the Swiss Education System

To assess whether the suggested competition or crowding out process seems plausible in the present context, it is necessary to take a closer look at how the education system functions regarding the transition from primary to secondary education. In Switzerland, children usually enter the education system by the age of 4, starting with two years of kindergarten, followed by six years of primary school. Based on their educational performance (grades in math and, depending on the region they live in, either German, French or Italian), teachers assign students to one of the different secondary education tracks. This initial assignment is not entirely binding and is discussed with students and their parents. If parents do not agree with the assignment, the initial choice will be reevaluated and in the most extreme case will be decided by an external authority (e.g., the supervisory school authority). The available tracks consist of a lower and a higher, more demanding alternative. In some cantons, there exists the possibility of entering the grammar school after sixth grade. Since this alternative usually involves additional admission examinations, students are nevertheless preliminarily assigned to one of the two tracks. The two main alternatives differ considerably regarding later educational opportunities, for example regarding access to higher education.

Furthermore, until completion of the three mandatory years of secondary education, there is no free school choice in Switzerland (apart from the marginal presence of private schools (Diem & Wolter, 2013). School catchment areas are defined by administrative neighborhood boundaries, with several neighborhoods constituting a catchment area. With that in mind, it is therefore likely that the available places per alternative are more or less fixed in each catchment area. This is also reflected at the aggregate level. During the last 20 years, the share of students in the lower and higher track of secondary education has stayed roughly constant with about 32% attending the less demanding track (Federal Statistical Office, 2017). This institutional setting suggests that crowding out processes are indeed likely to occur.

5. Data & Methodology

In the following, spatial econometric models are briefly outlined for readers who are not yet familiar with the methodology. This is followed by a presentation of the data used to test the outlined hypotheses.

5.1. A spatial econometric approach

The basic idea of any spatial econometric model is to allow the values for observation i to depend on other units j: $y_i = f(y_j),\ i = 1, \dots, n;\ i \neq j$ (LeSage & Pace, 2009). As an example, the value of one's house would depend on the value of neighboring houses, because it indicates whether the house is in a 'good' neighborhood or not. One's neighbors' investments in their houses will therefore not only increase the value of their house but also of mine (e.g., Holly, Pesaran, & Yamagata, 2010). In the present context, the idea is to use such mutual dependence instead of assessing contextual or compositional influences by means of aggregated, fixed measures (e.g., proportion of neighbors with tertiary degrees). Focusing on the propensity of attending the higher, more advantageous track, the assumed effect of others' behavior and beliefs, more specifically, their educational motivation, is modeled by introducing a (spatial) dependence between observations. This results in mutual feedback between units. In contrast to common hierarchical models, spatial econometrics enables us to model the effects of intertwined social action dynamically, beyond a solely geographical notion of space (Beck, Gleditsch, & Beardsley, 2006).

For the present purpose and using a latent variable representation, where Y_i denotes the outcome for subject i and $Y_i = \begin{cases} 1, & if\ Y_i^* > 0 \\ 0, & otherwise \end{cases}$, the equation of interest can be written in matrix notation as

$$\boldsymbol{Y}^* = \rho \boldsymbol{W} \boldsymbol{Y}^* + \boldsymbol{W} \boldsymbol{X}_{\boldsymbol{a} \in \boldsymbol{A}} \boldsymbol{\theta} + \boldsymbol{X}_{\boldsymbol{b} \in \boldsymbol{B}} \boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{4}$$

$\boldsymbol{Y}^*$ represents an unobserved, continuous random vector for the $i = 1, 2, \dots, n$ observations (here: the propensity for a transition to the higher track), and $\boldsymbol{X}$ is a $n \times k$ matrix of k independent variables, for example parental social background or student's sex, with $\boldsymbol{\beta}$ as a vector of the corresponding effects. The error vector $\boldsymbol{\varepsilon}$ is assumed to follow either a multivariate normal (probit model) or a multivariate logit distribution. The spatial probit or logit model differs from the non-spatial setting because of the introduction of spatial dependence through the weights matrix $\boldsymbol{W} \in \mathbb{R}^{n \times n}$ (LeSage & Pace, 2009). The $n \times n$ weights matrix $\boldsymbol{W}$ captures the interdependence between the observations and is usually row standardized.[1] The corresponding scalar ρ is referred to as spatial lag and reflects spillover effects through the dependent variable, i.e. from others' actual transitions to the higher track. Similarly, the parameter vector $\boldsymbol{\theta}$ denotes direct spillover effects of explanatory variables $\boldsymbol{X}_j$ on Y_i^* for individuals i and j, $i \neq j$. However, when looking at the reduced form of equation (4), it becomes apparent that, apart from these direct spillover effects, there are also indirect spillovers of $\boldsymbol{X}$ through ρ (i.e., effects of others' independent variables that work through the relationship between the dependent variables of two students, depicted by the multiplication with the so called 'spatial multiplier' $(\boldsymbol{I} - \rho\boldsymbol{W})^{-\mathbf{1}}$).

$$\boldsymbol{Y}^* = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\boldsymbol{W}\boldsymbol{X}_{\boldsymbol{a}\in\boldsymbol{A}}\boldsymbol{\theta} + \boldsymbol{X}_{\boldsymbol{b}\in\boldsymbol{B}}\boldsymbol{\beta} + \boldsymbol{\varepsilon}) \tag{5}$$

[1] With row-standardization, the weights for the dependence between observation i and its j^{th} neighbor writes as $w_i^* = w_i / \sum_{j=1}^{n} w_j$, that is, the weights sum to 1 for each observation.

Unlike common applications of spatial logit or probit models (e.g., Calabrese & Elkink, 2014), this paper lays the focus on the effect of $\boldsymbol{\theta}$ rather than on ρ . These effects capture the interdependence that takes place through the theoretical parameters (i.e., assessment of benefits, costs, likelihood of success, importance of status maintenance, instrumentality, educational motivation, and investment risk). It also follows that the vectors $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$ do not necessarily relate to the same set of explanatory variables $\boldsymbol{X}$. More specifically, the spatially lagged (i.e., interdependent) covariates are a subset of all independent variables: $\boldsymbol{X}_{\boldsymbol{a}\in\boldsymbol{A}} \subseteq \boldsymbol{X}_{\boldsymbol{b}\in\boldsymbol{B}}$.

To determine the extent, source and direction of any spatial interdependence, the different theoretical parameters are tested univariately using a Moran's I test statistic, the spatial equivalent to the correlation coefficient (Cressie, 2015). The next step is to test whether the observed interdependence could be attributed to a spatial lag or a spatial error process using Robust Lagrange Multiplier tests after ordinary (least squares) regression models (LeSage & Pace, 2009). Finally, the model in equation (4) is estimated using a Maximum Likelihood estimator that jointly maximizes ρ, $\boldsymbol{\theta}$, and $\boldsymbol{\beta}$. In what follows, the data and the operationalization of the relevant theoretical constructs are presented before turning to the empirical assessment of the two hypotheses.

5.2 Data & Operationalization

For the empirical assessment of the elaborated model, data from a research project on the educational attainment of elementary students at the transition to secondary school after completing 6th grade is used.[2] The investigation took place in two major Swiss cities (Bern and Zurich). Students (aged 12 at the transition to secondary school) and their parents were interviewed two times—while they were in the 5th and in the second half of 6th grade. While all students filled in the paper questionnaires during class, approximately 63% of all parents in the first wave and 52% in the second wave returned completed questionnaires. Although it is generally agreed that missing values due to item or unit non-response always introduce bias into spatial econometric models (due to the spatial multiplier $(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}$ and the associated relative weights in $\boldsymbol{W}$), there is

---

[2] Determinants of the Educational Success of Migrants in the Swiss Schooling System (DEBIMISS), funded by the Swiss National Science Foundation, Grant No. 121610 (http://p3.snf.ch/Project-121610).

less agreement on what should be done to deal with the issue (Kelejian & Prucha, 2010; LeSage & Pace, 2004). Given the lack of adequate imputation methods for the present purpose of a spatial probit model with lagged independent variables, an ad hoc solution was used. Missing values were imputed non-spatially using chained equations (White, Royston, & Wood, 2011), creating 50 imputed datasets which were then collapsed, resulting in 690 observations. On the one hand, this causes our estimates to be too liberal in the case of imputed values of independent variables, increasing the chance of an erroneous rejection of the null hypothesis. However, none of the theoretical constructs were imputed and missing values mainly occurred on students' grades in math and German, as some teachers did not report them in both waves. Further missing values occurred on some demographic characteristics, although to a lesser extent. On the other hand, regarding spatially lagged processes, the estimates will tend to be too conservative, as the spatial interdependence is not accounted for in the imputation step. These limitations should be kept in mind when interpreting the effects. Moreover, model estimates based on listwise deletion as well as estimates with additionally added uncertainty to imputed values by means of a random draw of the respective (normal) error distribution are presented in the appendix (Tables A4 and A5).

While Table A1 in the appendix provides summary statistics for all the measures used in the analyses, in the following, the key concepts shall be discussed in more detail. As already introduced in section 4, the dependent variable consists of a binary choice between a lower and a higher, more demanding, track. To capture institutional differences between the two cities (e.g., the availability of a grammar school), we additionally control for city fixed effects.[3] The main determinants of assigning a student to one of the two different alternatives are his or her grades in both math and German. There is, however, some room left for teachers and parents to negotiate the final choice of a secondary school track. Following Boudon (1974), students' social and migration backgrounds (operationalized as parental class position, according to the Erikson-Goldthorpe-Portocarero class scheme and language spoken at home) are included to capture any remaining social selectivity in the

[3] Since only 266 of the total 690 cases are from Bern and there would have been an empty cells and quasi-complete separation problem, separate models for the two cities were not estimated.

transition to secondary school. Furthermore, gender and the financial situation of the household are included as additional controls.

Additionally to students' educational performance, the parental assessment of the benefits, costs, success probability, importance of status maintenance and instrumentality of the higher track are added to the model to capture secondary effects (Breen & Goldthorpe, 1997). Using Likert scales[4] for all of the following concepts, the expected benefits (B) are measured as the parental judgment on whether they think their children would get a well-paid job as a result of each of the educational alternatives (i.e., the lower or the higher school track in secondary school). Similarly, the costs (C) are assessed as their rating of in how far each of the alternatives would constitute a financial burden. Furthermore, parents estimated how likely it would be for their children to successfully be able to complete the different tracks (π). They also rated the

[4] All items consist of 5 point scales, ranging from -2, "not at all", to 2, "most certainly". However, in the case of the parental assessment of different likelihoods (π and p), these scales were recoded into the range from 0.1 to 0.9. On the one hand, using 0.1 and 0.9, rather than 0 and 1, as endpoints was necessary to prevent division by 0 in some of the theoretical constructs (C_{ik}/p_{ik}). On the other hand, it also seems to be an adequate reflection of how people assess probabilities in the real world (Best, 2007).

importance of status maintenance in general ($-SD$), as well as the likelihood of their children ending up with an occupation as prestigious as their own for each of the tracks (p). Based on these items, individual i's educational motivation for track k, $A_{ik} = [B_{ik} + (p_{ik} \times -SD_i)]$, and the associated investment risk, C_{ik}/p_{ik}, were calculated.

As the data not only permit the identification of students within classrooms ($N_{Classrooms} = 75$) and schools ($N_{Schools} = 54$), but also within neighborhoods ($N_{Neighborhoods} = 33$), the latter information was used to construct the above introduced weights matrix $\boldsymbol{W}$. Two observations, i and j, are considered to be neighbors if they belong to the same neighborhood, $k = 1, \dots, 33$. A binary coding was used to construct the adjacency matrix $\boldsymbol{W}$ with $w_i \in \boldsymbol{W} = \begin{cases} 1, & if\ i \in k \\ 0, & otherwise \end{cases}$. To obtain consistent estimates, cases with less than three neighbors were omitted from the analysis.[5] Note that this definition of neighbors still relies on administrative

[5] This led to the deletion of two observations who are mutual neighbors. Both have an advantageous social background (EGP I and II), good grades in math and German and both will attend the upper track in the next school year. Since they do not deviate from the general pattern and given the small number of deleted cases, results can be expected to be robust to the omission of these two cases.

boundaries and therefore is not free of the therewith associated problems (Lupton & Kneale, 2012). These administrative boundaries relate to entities that consist of 11'962 people on average, although they tend to be somewhat smaller in Bern than in Zurich. The neighborhoods in the two cities, however, are comparable in terms of demographic composition and variation as well as social segregation (Zangger, 2015). Although it can be assumed that parents within schools know each other—at least partially—this is not necessarily the case at the wider neighborhood level. Therefore, neighbors, as defined in our case, should rather be understood as a sample of parents of 12-year-old children who one would expect to have contact with each other within their neighborhood. The possible confusion of school and neighborhood effects as well as the dependence of the results on the parameterization of $\boldsymbol{W}$ is therefore examined by using alternative specifications of the weights matrix. As noted above, schools have specific catchment areas and these coincide with neighborhood boundaries. Therefore, models with bigger weights to neighbors with children in the same school (getting twice the weight) are additionally estimated. Furthermore, models in which the weights matrix is constructed at the school rather than the neighborhood level are presented as a further robustness check. While each observation has, on average, 20.9 neighbors when using administrative neighborhood boundaries, this number is reduced to 12.8 neighbors if the weights' matrix is constructed at the school level exclusively. Finally, we control for the classroom level educational achievement of all other students to distinguish between potential effects of the interdependence in the neighborhood and schools and those of the more immediate classroom context.

6. Results

In the following, the amount of spatial interdependence of the theoretical parameters, as introduced in equation (3), is examined. Furthermore, its consequences in terms of the propensity to be assigned to the higher track of secondary education are evaluated. This stepwise approach enables a rigorous testing of the suggested mechanism of neighborhood effects on educational attainment.

6.1. Spatial Association of the Theoretical Parameters

It was argued above, that the interdependence at the neighborhood level should mainly take place through the parameters that influence people's educational motivation for alternative k, that is $B_k + p_k \times (-SD)$, and therein especially through the benefits B_k and the instrumentality p_k. Furthermore, it was suggested that the assessment of the likelihood π_k of successfully completing a given alternative k could also be shaped by the interaction with others. The subjective evaluation of the direct costs C_k and the importance of status maintenance $(-SD)$, however, should be less influenced by others' judgments of the same parameters.

As a first test of these assumptions, Figure 1 presents Moran's I test statistics for the theoretical parameters, 1) giving the same weight to all neighbors (circles), 2) giving bigger weight to neighbors with children in the same school (squares), and 3) for the weights matrix conceptualized entirely at the school level (triangles). Positive values depict a positive association of adjacent units, as defined by $\boldsymbol{W}$, whereas negative values indicate a negative association (Cressie, 2015). As expected, an individual i's educational motivation is quite strongly related to the motivation of his or her neighbors j. This interdependence can thereby be attributed to the spatial association in the instrumentality and, to a lesser extent, to the expected benefits of the different tracks, as well as to the importance of status maintenance. The absence of any interdependence in people's evaluations of the success probability, however, is rather unexpected. Similarly, the interdependence of the direct costs between neighbors was not expected. Finally, the univariate dependence is roughly the same for all three conceptualizations of the weights matrix, except for a substantially lower positive interdependence of the educational motivation for the case in which only other parents in the same school are considered. However, this first impression of (in)dependence of the theoretical parameters might merely reflect heterogeneous associations for different subgroups. Figure 1 does not provide any information about whether the dependence is due to unobserved selection processes or whether the individual assessment is indeed shaped by other parents in the same neighborhood. The finding of no univariate dependence in the case of the success probability, for example, might therefore reflect different signs in the association for different groups (e.g. high vs. low social status) in different neighborhoods.

Figure 1 about here

In this regard, not only do theory and previous research suggest that $B, C, \pi, p,$ and $(-SD)$ differ according to individual social origin (Becker, 2003; Stocké, 2007) but the resources associated with social origin also determine residential choices and mobility (Galster & Hedman, 2013).

The observed spatial association might thus be the reflection of differences in individual tastes and resources (selection bias). The theoretical parameters were therefore regressed on social class, gender, language spoken at home, household's financial situation, and city of residence (Table A2 in the appendix). The residuals of these regressions were then tested for any remaining spatial dependence (first column of Table 2), as well as its source. To this end, robust Lagrange Multiplier tests (RLM), testing for the alternative of spatial autoregression (spatial lag) and spatial autocorrelation (spatial error), were used (LeSage & Pace, 2009). On the one hand, a spatial dependence through the errors instead of through the examined characteristics would suggest a potential omitted variable or selection bias problem (LeSage & Pace, 2009). On the other hand, a spatial lag process (i.e., an influence of others' assessments) would strengthen the hypothesis regarding the assumed interdependence.

As reported in Table 2, the observed interdependence is considerably reduced and—comparing the corresponding χ^2 statistics of the RLM tests—can generally be attributed to spatial lag processes. Hence, there is evidence for a positive interdependence and spillover effects in the case of educational motivation, which work through both the benefits and the instrumentality (third column of Table 2). On the other hand, there is almost no evidence for such spillovers in the assessment of the costs and the importance of status maintenance. Note, however, that it is not possible to completely rule out a potential selection effect as indicated by the (although consistently weaker) RLM for the spatial error alternative.

Table 2 about here

Finally, using linear spatial autoregressive models (i.e., models with the spatially lagged theoretical parameter under examination as a right-hand side variable; LeSage & Pace, 2009)[6], the same pattern emerges. As reported in Figure 2, there is evidence for significant and positive spillover effects for people's educational motivation, the associated expected benefits and the instrumentality of different educational tracks. Thus, independently of individual characteristics and resources, people's educational motivations seem to be mutually dependent within neighborhoods (Hypothesis 1): Having motivated neighbors is consistently associated with being motivated to send one's own kids to

[6] These models are of the form $\boldsymbol{Y} = \rho \boldsymbol{W}\boldsymbol{Y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$.

the higher track as well.[7] However, whether this mutual positive influence is due to interacting with one's neighbors or merely a response to the observation of their behavior cannot be assessed based on the present data. Nevertheless, these results are almost independent of the parameterization of $\boldsymbol{W}$. While the effects are somewhat reduced when only peers' parents within the same school (triangles) are considered, the most precise estimates are obtained at the neighborhood level, giving an equal weight to all interdependent observations (circles). As a next step, the extent to which children's educational attainments are shaped by the observed interdependence at the neighborhood level is examined.

6.2. A Spatial Probit Model of Educational Inequalities

To what extent does the educational motivation of neighbors affect the chances that one's own child will attend the higher track of secondary school? To answer this question, models with indirect and direct spillover effects (i.e., $(\boldsymbol{I}-\rho\boldsymbol{W})^{-1}(\boldsymbol{X}_{\boldsymbol{b}\in\boldsymbol{B}}\boldsymbol{\beta}+\boldsymbol{\varepsilon})$ and $(\boldsymbol{I}-\rho\boldsymbol{W})^{-1}(\boldsymbol{W}\boldsymbol{X}_{\boldsymbol{a}\in\boldsymbol{A}}\boldsymbol{\theta}+\boldsymbol{X}_{\boldsymbol{b}\in\boldsymbol{B}}\boldsymbol{\beta}+\boldsymbol{\varepsilon})$, respectively) were estimated. In Table , the effects are reported as the

[7] Using a direct measure of parental aspirations (the highest degree they would want their child to obtain), rather than the theoretically elaborated educational motivation, results in the same positive dependence (not reported).

odds $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\theta}}$ of attending the higher instead of the lower track, conditional on ρ. Again, results for different parameterizations of $\boldsymbol{W}$ are presented.

Figure 2 about here

As mentioned above, the main determinant of the assignment to one of the two tracks is a student's prior educational achievement (the pseudo-R^2 of bivariately regressing the transition onto students' grades in the 6th grade is 0.58 in a non-spatial model). Nevertheless, there is still room for parental influences, as reported in the significant coefficients for the benefits B, the likelihood of success π, and parental educational motivation $U + p \times (-SD)$, even after additionally controlling for individual social background, resources and educational achievement at the classroom level (which, notably, has a negative effect). Since ρ, the autoregressive coefficient, is far from being significant in any model, there is no evidence for indirect spillover effects that work through the dependent variable. However, significant direct effects of one's neighbors' educational motivation ($\theta_{B+c\times(-SD)}$) are detected.[8] While a positive

[8] It should be mentioned that models with lags of the single additive parameters $B, \pi, C, p,$ and $-SD$ could not be estimated due to quasi complete separation (Agresti, 2013), once

interdependence in neighbors' educational motivation was found before, this dependence translates into a negative effect when focusing on the transition to the higher, more advantageous track. The higher other parents' educational motivation for the higher track in the neighborhood, the less likely it is that one's own child will attend it. This effect, which works in addition to the individual assessment of the theoretical parameters and independently of own and others' achievement, as well as a variety of social background characteristics, is consistently found across all parameterizations of $\boldsymbol{W}$. Furthermore, in the case in which only parents of peers within the same school are considered, there is a negative effect of others' assessment of the investment risk (last column of Table 2). So far, we have thus seen indications of both positive (increasing educational motivation) as well as negative neighborhood effects (decreasing likelihood of attending the higher track).

Table 3 about here

again reflecting the determining effect of grades in the assignment to one of the tracks and the rather small sample size.

However, the negative effect of neighbors' educational motivation might merely reflect the unexpected negative effect of individual educational motivation for the higher track. As can be inferred from the first, fourth, and seventh columns in Table 2, this negative effect of individual educational motivation reflects the assessment of the expected benefits: The higher parents evaluate the benefits in terms of getting a well-paying job after completing the higher track, the lower the probability their children will attend said track. While this effect could be caused by a subgroup of parents who are highly motivated but whose children do not show the necessary performance, further examination shows that the effect is conditional on parents' evaluation of the other alternatives. Once the expected benefits of the lower track are controlled for, the negative individual effect, $B + p \times [-SD]$, disappears, while the interdependence effect, $\theta_{B+p\times(-SD)}$, remains unchanged (Table A3 in the appendix). This most likely reflects the fact that parents' assessment of the expected benefits was collected at a time when some of them already knew which track their child would attend in the next school year. They might have therefore adjusted their rating accordingly, especially in the case of Zurich, where some of the students would attend the grammar school, which can be regarded as an even more advantageous alternative.

However, one should note that this potential feedback from the actual transition to the assessment of the benefits does not derogate the theoretically implied interdependence, as also demonstrated in the persistent lagged effect. Moreover, the negative effect of other students' achievement at the classroom level suggests an analogous competition at the more immediate level (see Table A3 in the appendix). As a final sensitivity test, considering social interdependence only at the classroom level (i.e., constructing the weights matrix at this more immediate level) leads to similar but considerably weaker and only marginally significant effects (not reported). Since the main argument is based on the interplay of a spatially dependent evaluation of different educational alternatives within neighborhoods and fixed larger school catchment areas, this finding strengthens an interpretation in line with the theoretical considerations.

Summing up, we first demonstrated a positive interdependence between neighbors' educational motivation (Hypothesis 1). Second, it was demonstrated how this interdependence translates into the suggested negative effects at the transition to the more advantageous track, due to a—in the short run—fixed number of seats within prespecified school catchment areas that recruit pupils from adjacent neighborhoods

(Hypothesis 2). Thus, we find a complex puzzle of simultaneously positive and negative externalities of one's neighbors that shape not only the parental assessment of benefits and attendance probabilities of different educational alternatives but also students' transitions to one of the available tracks. Furthermore, the effects of others' assessments are generally slightly stronger when only parents of children within the same school are considered instead of from the entire neighborhood. This could be seen to suggest that we are partly dealing with a school rather than a neighborhood effect. At the same time, however, the estimates at the neighborhood level are more precise, indicating that there is not much additional heterogeneity at this higher level. Moreover, the theoretical argument suggested a complex interaction of school and neighborhood effects. Since neighborhoods are the basis for prespecified school catchment areas, the suggested competition for the limited places in the case of the more advantageous higher track necessarily works through both schools and neighborhoods in the present context. Finally, although not shown, comparable results are obtained when focusing on the lower rather than the higher track. While the extent of the interdependence of the expected benefits and the instrumentality is almost identical, it also translates into a positive lagged effect of neighbors' educational motivation for the lower track on the propensity of attending this track. This further strengthens the interpretation of the above results in terms of social closure effects and competition for the more demanding and advantageous track.

7. Discussion

While there is an ever-growing body of research on neighborhood effects on different forms of life chances (e.g., Galster, 2012; Oakes et al., 2015; Sampson et al., 2002), the underlying theoretical concepts still rely on rather broad theoretical assumptions, such as collective socialization or the epidemic spread of norms. Furthermore, the suggested social mechanisms are often only tested indirectly, using empirical modeling strategies that are not in line with the theoretical framework. More specifically, the existing literature fails to articulate and model the assumed social interdependence in terms of individual social action.

Using the transition to secondary education in Switzerland as an example, this paper demonstrates how a rational action framework (Breen & Goldthorpe, 1997) can fruitfully be extended to incorporate a channel of neighborhood effects on educational attainment. On the one hand, an additional, contextual path for the reproduction of educational inequalities in terms of individual social action is proposed. On the other hand, modeling the social interdependence using spatial econometrics sheds further light on potential mechanisms of neighborhood effects. Using spatial autoregressive linear and probit models, it is demonstrated how people adjust their expectations of the benefits and instrumentality of different educational tracks according to their neighbors' views. Furthermore, it is shown how this interdependence then shapes their educational choices. As expected, the main source of interdependence at the neighborhood level is identified in parents' educational motivations $(B + p \times (-SD)$, rather than in the investment risk (C/π). This interdependence cannot be attributed to individual resources or tastes and suggests a spillover from adjacent observations (i.e., their neighbors). However, negative effects emerge when it comes to the consequences of said interdependence in terms of students' transition to secondary school. Facing highly motivated neighbors is associated with lower chances of attending the more advantageous track. Taken together with the observed negative impact of peers' achievement at the classroom level, this finding suggests that competition processes are at work (Galster, 2012; Sacerdote, 2011). As educational motivation increases with social status (Becker, 2003; Breen & Goldthorpe, 1997), this result does not directly challenge the general finding of a positive influence of high status neighborhoods on educational outcomes (e.g., Ainsworth, 2002; Andersson & Malmberg, 2015). However, it nevertheless stresses the importance of considering non-uniform neighborhood influences for different social groups. Given the strong association between individual resources, educational achievement, educational motivation and residential mobility (Galster & Hedman, 2013), this suggests further obstacles for those with less fortunate backgrounds who are facing highly competitive, resource-rich peers.

Although different steps have been taken to make sure that we are indeed dealing with social and spatial interdependence at the neighborhood level, a potential selection problem cannot be completely rejected. In this respect, however, the estimated spatial Durbin models are an especially promising approach, since it has been shown that the estimation of spatial spillover effects in these kind of models are quite robust to omitted variable and selection bias (LeSage & Pace, 2009). Nevertheless, rather than documenting a causal neighborhood effect, we describe a cross-sectional spatial interdependence in neighbors' educational decision making. Furthermore, the testing of different specifications of the weights matrix $\boldsymbol{W}$, reflecting the proposed interdependence in the empirical models, rendered slightly stronger, although less precise, effects when only parents within the same school rather than all neighbors were considered. In line with the theoretical argument (approximately fixed number of places for the more advantageous alternative), it is thus possible that the documented neighborhood effect works—at least partially—through schools rather than directly from one neighbor to another. Similarly, using spatial econometric models might also be a source of additional, namely aggregation, bias. In this regard, it is possible that results are driven not only by the general specification of the underlying weights matrix $\boldsymbol{W}$ but also by the relative weights w_{ij}. However, this issue was addressed by focusing solely on cases with at least three neighbors. However, this last point does not diminish the relevance of spatial econometric models for sociological research. They are by no means restricted to a merely geographical notion of space (Beck et al., 2006). Instead, they allow us to include mutual dependence and feedback processes across social actors. It is for this reason that spatial econometric models are not only a promising strategy to dynamically model contextual and compositional effects (as opposed to the common hierarchical models), but they more generally allow for the incorporation of the interdependence suggested by many theories that build on social action and aligned decision making.

Finally, the finding of simultaneous positive and negative neighborhood effects strongly speaks against linear-in-means interpretations of neighborhood effects in general (Sacerdote, 2011; Sharkey & Faber, 2014). Instead, future research should consider various, and even competing, social mechanisms simultaneously. Furthermore, these results advocate for the importance of policies that abandon the view of atomized individuals. Hence, successful interventions for reducing educational inequalities should carefully examine the possible consequences of multiplier effects within a neighborhood context (Durlauf & Ioannides, 2010). While such policies might fruitfully make use of such social and spatial multipliers (Lupton & Kintrea, 2011), they also raise concerns. As has been demonstrated, pursuing the best for one individual might lower the life chances of others.

6. Bibliography

Agresti, A. (2013). *Categorical Data Analysis*. Hoboken, NJ: Wiley.

Ainsworth, J. W. (2002). Why Does It Take a Village? The Mediation of Neighborhood Effects on Educational Achievement. *Social Forces*, *81*(1), 117–152.

Andersson, E., & Malmberg, B. (2015). Contextual effects on educational attainment in individualised, scalable neighbourhoods: Differences across gender and social class. *Urban Studies*, *52*(12), 2117–2133.

Andersson, E., & Subramanian, S. V. (2006). Explorations of neighbourhood and educational outcomes for young Swedes. *Urban Studies*, *43*(11), 2013–2025.

Becker, R. (2003). Educational Expansion and Persistent Inequalities of Education. *European Sociological Review*, *19*(1), 1–24.

Beck, N., Gleditsch, K. S., & Beardsley, K. (2006). Space Is More than Geography: Using Spatial Econometrics in the Study of Political Economy. *International Studies Quarterly*, *50*(1), 27–44.

Best, H. (2007). Die Messung von Nutzen und subjektiven Wahrscheinlichkeiten. Ein Vorschlag zur Operationalisierung der Rational Choice Theorie. *Methoden Daten Analysen*, *1*(2), 183–212.

Boudon, R. (1974). *Education, Opportunity, and Social Inequality: Changing Prospects in Western Society*. New York: John Wiley.

Brännström, L. (2008). Making Their Mark: The Effects of Neighbourhood and Upper Secondary School on Educational Achievement. *European Sociological Review*, *24*(4), 463–478.

Breen, R., & Goldthorpe, J. H. (1997). Explaining Educational Differentials: Towards a formal rational action theory. *Rationality and Society*, *9*(3), 275–305.

Breen, R., & Jonsson, J. O. (2005). Inequality of Opportunity in Comparative Perspective: Recent Research on Educational Attainment and Social Mobility. *Annual Review of Sociology*, *31*, 223–243.

Breen, R., Luijkx, R., Muller, W., & Pollak, R. (2010). Long-term Trends in Educational Inequality in Europe: Class Inequalities and Gender Differences. *European Sociological Review*, *26*(1), 31–48.

Burt, R. S. (2000). The network structure of social capital. *Research in Organizational Behavior*, *22*, 345–423.

Calabrese, R., & Elkink, J. A. (2014). Estiamtors of Binary Spatial Autoregressive Models: A Monte Carlo Study. *Journal of Regional Science*, *54*(4), 664–687.

Carbonaro, W. J. (1998). A Little Help from My Friend's Parents: Intergenerational Closure and Educational Outcomes. *Sociology of Education*, *71*(4), 295–313.

Chetty, R., Hendren, N., & Katz, L. F. (2016). The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment. *American Economic Review*, *106*(4), 855–902.

Clampet-Lundquist, S., & Massey, D. S. (2008). Neighborhood Effects on Economic Self-Sufficiency: A Reconsideration of the Moving to Opportunity Experiment. *American Journal of Sociology*, *114*(1), 107–143.

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*, *94*(Supplement), 95–120.

Coleman, J. S., Hoffer, T., & Kilgore, S. (1982). *High School Achievement. Public, Catholic, and Private Schools Compared*. New York: Basic Books.

Crane, J. (1991). The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing. *American Journal of Sociology*, *96*(5), 1226–1259.

Cressie, N. A. (2015). *Statistics for Spatial Data*. New York: Wiley.

Diem, A., & Wolter, S. C. (2013). Who is Afraid of School Choice. *Swiss Journal of Sociology*, *39*(1), 57–80.

Duncan, O. D., Haller, A. O., & Portes, A. (1968). Peer Influences on Aspirations: A Reinterpretation. *American Journal of Sociology*, *74*(2), 119–137.

Durlauf, S. N. (2004). Neighborhood Effects. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2173–2242). Amsterdam: North Holland.

Durlauf, S. N., & Ioannides, Y. M. (2010). Social Interactions. *Annual Review of Economics*, *2*(1), 451–478.

Erikson, R., & Jonsson, J. O. (1996). Explaining Class Inequality in Education. The Swedish Test Case. In R. Erikson & J. O. Jonsson (Eds.), *Can Education Be Equalized? The Swedish Case in Comparative Perspective* (pp. 1–63). Boulder, Colorado: Westview Press.

Esser, H. (1999). *Soziologie. Spezielle Grundlagen. Band 1. Situationslogik und Handeln*. Frankfurt am Main: Campus Verlag.

Federal Statistical Office. (2017). Selektion auf der Sekundarstufe I nach Schultyp. Retrieved from https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/bildungsindikatoren/bildungssystem-schweiz/themen/bildungsverlaeufe/selektion-sekundarstufe.assetdetail.2924648.html

Galster, G. C. (2002). An economic efficiency analysis of deconcentrating poverty populations. *Journal of Housing Economics*, *11*(4), 303–329.

Galster, G. C. (2012). The Mechanism(s) of Neighbourhood Effects: Theory, Evidence, and Policy Implications. In M. Van Ham, D. Manley, N. Bailey, L. Simpson, & D. Maclennan (Eds.), *Neighbourhood Effects Research: New Perspectives* (pp. 23–56). New York: Springer.

Galster, G. C., & Hedman, L. (2013). Measuring Neighbourhood Effects Non-experimentally: How much do Alternative Methods Matter? *Housing Studies*, *28*(3), 473–498.

Garner, C. L., & Raudenbush, S. W. (1991). Neighborhood Effects on Educational Attainment: A Multilevel Analysis. *Sociology of Education*, *64*(4), 251–262.

Goux, D., & Maurin, E. (2007). Close Neighbours Matter: Neighbourhood effects on early performance at school. *The Economic Journal 117*, *117*(523), 1193–1215.

Hanushek, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does Peer Ability Affect Student Achievement? *Journal of Applied Econometrics*, *18*(5), 527–544.

Harding, D. J. (2003). Counterfactual Models of Neighborhood Effects: The Effect of Neighborhood Poverty on Dropping Out and Teenage Pregnancy. *American Journal of Sociology*, *109*(3), 676–719.

Holly, S., Pesaran, M. H., & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, *158*(1), 160–173.

Kauppinen, T. M. (2007). Neighborhood effects in a European city: Secondary education of young people in Helsinki. *Social Science Research*, *36*(1), 421–444.

Kauppinen, T. M. (2008). Schools as Mediators of Neighbourhood Effects on Choice Between Vocational and Academic Tracks of Secondary Education in Helsinki. *European Sociological Review*, *24*(3), 379–391.

Kelejian, H. H., & Prucha, I. R. (2010). Spatial models with spatially lagged dependent variables and incomplete data. *Journal of Geographical Systems*, *12*(3), 241–257.

Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica*, *75*(1), 83–119.

LeSage, J. P., & Pace, R. K. (2004). Models for spatially dependent missing data. *The Journal of Real Estate Finance and Economics*, *29*(2), 233–254.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Boca Raton: Taylor & Francis.

Leventhal, T., & Brooks-Gunn, J. (2000). The Neighborhoods They Live in: The Effects of Neighborhood Residence on Child and Adolescent Outcomes. *Psychological Bulletin*, *126*(2), 309–337.

Ludwig, J., Liebman, J. B., Kling, J. R., Duncan, G. J., Katz, L. F., Kessler, R. C., & Sanbonmatsu, L. (2008). What Can We Learn about Neighborhood Effects from the Moving to Opportunity Experiment? *American Journal of Sociology*, *114*(1), 144–188.

Lupton, R., & Kintrea, K. (2011). Can Community-Based Interventions on Aspirations Raise Young People's Attainment? *Social Policy & Society*, *10*(3), 321–355.

Lupton, R., & Kneale, D. (2012). Theorising and Measuring Place in Neighbourhood Effect Research: The Example of Teenage Parenthood in England. In M. Van

Ham, D. Manley, N. Bailey, L. Simpson, & D. Maclennan (Eds.), *Neighbourhood Effects Research: New Perspectives* (pp. 121–145). New York u.a.: Springer.

MacLeod, J. (2011). Ain't No Makin' It. Leveld aspirations in a low-income neighborhood. In D. B. Grusky & S. Szelényi (Eds.), *The Inequality Reader* (pp. 567–583). Boulder, Colorado: Westview Press.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies*, *60*(3), 531–542.

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, *39*(3), 517–558.

Morgan, S. L. (2001). Counterfactuals, Causal Effect Heterogeneity, and the Catholic School Effect on Learning. *Sociology of Education*, *74*(4), 341–374.

Musterd, S. (2005). Social and Ethnic Segregation in Europe: Levels, Causes, and Effects. *Journal of Urban Affairs*, *27*(3), 331–348.

Oakes, J. M. (2004). The (mis)estimation of neighborhood effects: causal inference for a practicable social epidemiology. *Social Science & Medicine*, *58*(10), 1929–1952.

Oakes, J. M., Andrade, K. E., Biyoow, I. M., & Cowan, L. T. (2015). Twenty Years of Neighborhood Effect Research: An Assessment. *Current Epidemiology Reports*, *2*(1), 80–87.

Page, L., Levy Garboua, L., & Montmarquette, C. (2007). Aspiration levels and educational choices: An experimental study. *Economics of Education Review*, *26*(6), 747–757.

Paulus, W., & Blossfeld, H.-P. (2007). Schichtspezifische Präferenzen oder sozioökonomisches Entscheidungskalkül? Zur Rolle elterlicher Bildungsaspirationen im Entscheidungsprozess beim übergang von der Grundschule in die Sekundarstufe. *Zeitschrift Für Pädagogik*, *53*(4), 491–508.

Rosenbaum, J. E. (1995). Changing the Geography of Opportunity by Expanding Residential Choice: Lessons from the Gautreaux Program. *Housing Policy Debate*, *6*(1), 231–269.

Roth, T. (2017). Interpersonal influences on educational expectations: New evidence for Germany. *Research in Social Stratification and Mobility*, *48*, 68–84.

Sacerdote, B. (2011). Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far? In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), *Handbook of the Economics of Education* (Vol. 3, pp. 249–278). Amsterdam: Elsevier.

Sampson, R. J. (2008). Moving to Inequality: Neighborhood Effects and Experiments Meet Social Structure. *American Journal of Sociology*, *114*(1), 189–231.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing “Neighborhood Effects”: Social Processes and New Directions in Research. *Annual Review of Sociology*, *28*, 443–478.

Sewell, W. H., & Armer, J. M. (1966). Neighborhood Context and College Plans. *American Sociological Review*, *31*(2), 159–168.

Sewell, W. H., Haller, A. O., & Portes, A. (1969). The Educational and Early Occupational Attainment Process. *American Sociological Review*, *34*(1), 82–92.

Sharkey, P., & Faber, J. W. (2014). Where, when, why, and for whom do residential contexts matter? Moving away from the dichotomous understanding of neighborhood effects. *Annual Review of Sociology*, *40*, 559–579.

Stocké, V. (2007). Explaining Educational Decision and Effects of Families' Social Class Position: An Empirical Test of the Breen Goldthorpe Model of Educational Attainment. *European Sociological Review*, *23*(4), 505–519.

Sykes, B., & Musterd, S. (2011). Examining Neighbourhood and School Effects Simultaneously: What Does the Dutch Evidence Show? *Urban Studies*, *48*(7), 1307–1331. https://doi.org/10.1177/0042098010371393

White, I. R., Royston, P., & Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine*, *30*(4), 377–399.

Wilson, W. J. (1987). *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago; London: The University of Chicago Press.

Wodtke, G. T., Elwert, F., & Harding, D. J. (2016). Neighborhood effect heterogeneity by family income and developmental period. *American Journal of Sociology*, *121*(4), 1168–1222.

Zangger, C. (2015). The Social Geography of Educational Achievement. Neighborhood, Class Composition, and the Educational Success of Elementary Students in Zurich, Switzerland. *Zeitschrift Für Soziologie*, *44*(4), 292–310.

Tables

Table 1: Overview parameters of interest

Parameter	Description
B	Subjectively expected benefits (likelihood of a well-payed job after completing the higher track)
C	Subjectively expected costs (extent to which higher track would constitute a financial burden)
π	Likelihood of success (probability of successfully graduating from higher track)
p	Instrumentality for status maintenance (likelihood of getting a job as prestigious as the job of one's parents after graduating from higher track)
$-SD$	Importance of status maintenance (importance parents attach to their child's acquiring a job as prestigious as their own)
$B + p \times [-SD]$	Educational motivation
C/π	Investment risk

Table 2: Residual spatial dependence

	Moran's I (SE)	RLM: Spatial Error (df)	RLM: Spatial Lag (df)	R^2
Benefits (B)				
***W**: Neighborhood*	0.038^{***} (0.012)	6.013^{*} (1)	11.099^{***} (1)	
***W**: Neighborhood & Schools*	0.038^{***} (0.012)	5.776^{*} (1)	10.631^{**} (1)	0.042
***W**: Schools*	0.034^{*} (0.016)	4.716^{*} (1)	7.228^{**} (1)	
Costs (C)				
***W**: Neighborhood*	0.003 (0.012)	0.055 (1)	0.184 (1)	
***W**: Neighborhood & Schools*	0.004 (0.012)	0.061 (1)	0.228 (1)	0.193
***W**: Schools*	-0.003 (0.016)	0.281 (1)	0.255 (1)	
pr(success) (π)				
***W**: Neighborhood*	-0.002 (0.012)	1.162 (1)	1.220 (1)	0.003

***W**: Neighborhood & Schools*	-0.001 (0.012)	0.917 (1)	0.945 (1)	
***W**: Schools*	0.011 (0.016)	0.244 (1)	0.185 (1)	
Instrumentality (p)				
***W**: Neighborhood*	0.032** (0.012)	13.792*** (1)	27.156*** (1)	
***W**: Neighborhood & Schools*	0.032** (0.012)	14.171*** (1)	27.495*** (1)	0.116
***W**: Schools*	0.035* (0.016)	10.137** (1)	18.246*** (1)	
Status Maintenance ($-SD$)				
***W**: Neighborhood*	0.008 (0.012)	1.655 (1)	2.752† (1)	
***W**: Neighborhood & Schools*	0.007 (0.012)	1.139 (1)	1.945 (1)	0.081
***W**: Schools*	0.005 (0.016)	0.175 (1)	0.299 (1)	
Educational Motivation ($B + p \times [-SD]$)				
***W**: Neighborhood*	0.047*** (0.012)	2.935† (1)	12.790*** (1)	
***W**: Neighborhood & Schools*	0.046*** (0.012)	2.651 (1)	11.511*** (1)	0.087
***W**: Schools*	0.040** (0.016)	2.377 (1)	6.500** (1)	
Investment Risk (C/π)				
***W**: Neighborhood*	-0.008 (0.011)	0.193 (1)	0.040 (1)	
***W**: Neighborhood & Schools*	-0.010 (0.012)	0.276 (1)	0.052 (1)	0.091
***W**: Schools*	-0.023† (0.016)	0.573 (1)	0.091 (1)	

Source: DEBIMISS, own calculations; N=690; Moran's I: One sided test, all other 2-sided tests; controlled for indv. class position, financial situation, gender, city and language spoken at home.
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Spatial probit estimates: Transition to higher track

	$\boldsymbol{W}$: Neighborhood			$\boldsymbol{W}$: Neighborhood & School			$\boldsymbol{W}$: School		
	Indirect		Direct	Indirect		Direct	Indirect		Direct
Benefits	-0.662***			-0.665***			-0.664***		
(B)	(0.151)			(0.151)			(0.152)		
pr(Success)	1.931***			1.926***			1.928***		
(π)	(0.563)			(0.563)			(0.565)		
Costs	-0.025			-0.022			-0.019		
(C)	(0.099)			(0.099)			(0.099)		
Instrumentality	-0.334			-0.335			-0.356		
(p)	(0.574)			(0.574)			(0.575)		
Status Maintenance	-0.023			-0.021			-0.020		
$(-SD)$	(0.072)			(0.072)			(0.072)		
Educ. Motivation		-0.241***	-0.198**		-0.241***	-0.198**		-0.241***	-0.219**
$(B + p \times [-SD])$		(0.070)	(0.072)		(0.070)	(0.072)		(0.069)	(0.074)
Investment Risk		-0.006	0.001		-0.006	-0.000		-0.007	-0.007
(C/π)		(0.039)	(0.040)		(0.039)	(0.040)		(0.039)	(0.040)
Lagged Terms:									
$\boldsymbol{\theta_{B+p\times(-SD)}}$			-0.779**			-0.713**			-0.886***
			(0.274)			(-0.271)			(0.238)
$\boldsymbol{\theta_{C/\pi}}$			-0.087			-0.125			-0.257*
			(0.138)			(0.134)			(0.131)
Spatial Lag (ρ)	−0.000	-0.001	-0.001	0.001	-0.000	0.000	0.005	0.003	-0.007
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)	(0.009)
AIC	269.15	290.75	283.60	269.16	290.75	283.9	269.16	290.75	271.83
N	690	690	690	690	690	690	690	690	690

Source: DEBIMISS, own calculations; Controlled for parental social class, language spoken at home, sex, financial situation, city, grade in math and German, and educational achievement of other students at the classroom level; Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figures

Figure 1: Univariate Spatial Association

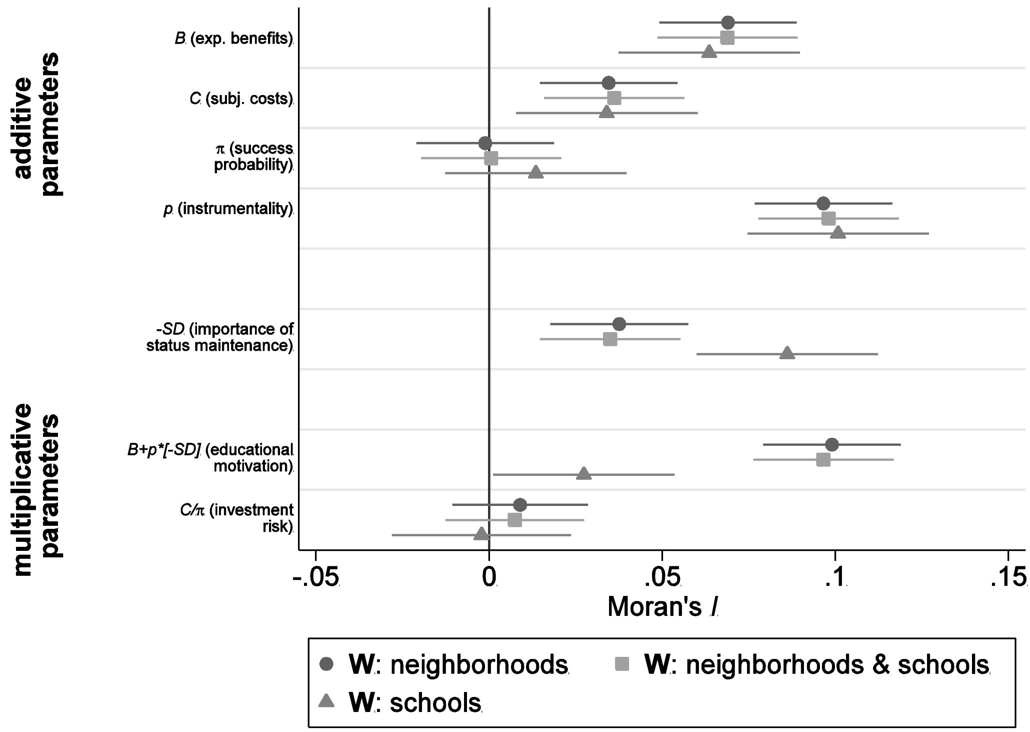
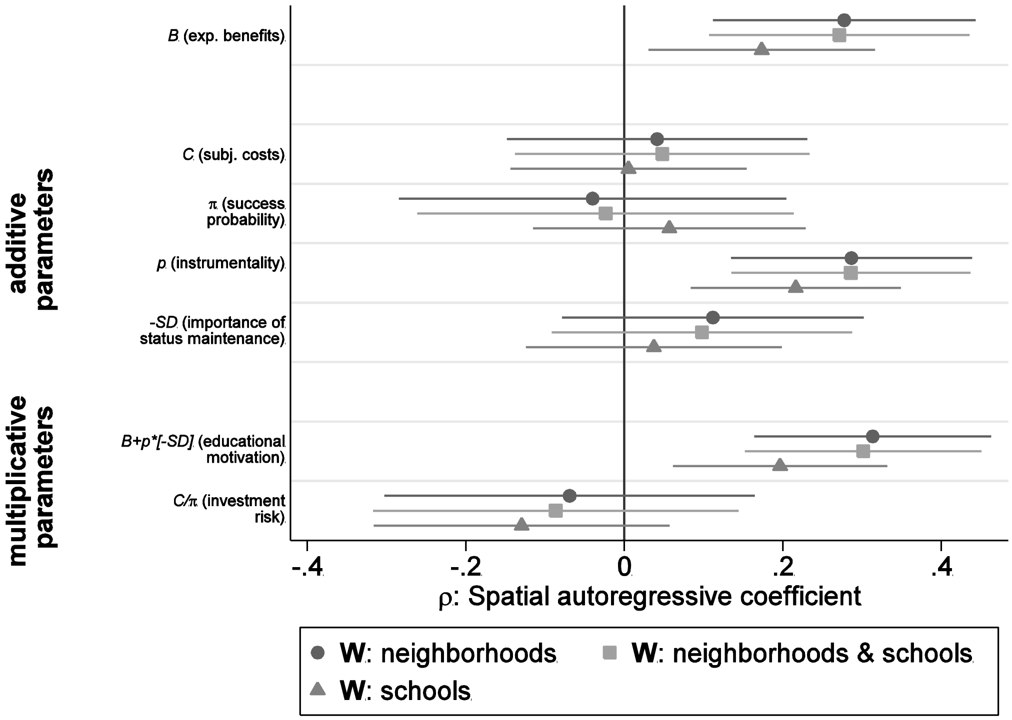


Figure 2: Spatial Autoregression of the Theoretical Parameters



Appendix

Table A1: Summary Statistics

Variable	Obs.	Mean	Min.	Max.
Transition to secondary school				
Higher vs. lower track	690	.778	0	1
Theoretical parameters				
Benefits (B)				
Higher track	690	.678	-2	2
Costs (C)				
Higher track	690	-.862	-2	2
Likelihood of success (π)				
Higher track	690	.690	.1	.9
Importance of status maintenance ($-SD$)	690	.354	-2	2
Instrumentality (p)				
Higher track	690	.637	.1	.9
Educational motivation ($B + p \times [-SD]$)				
Higher track	690	.941	-3.5	3.8
Investment risk (C/π)				
Higher track	690	-1.514	-20	20
Controls				
Math 6th grade	690	4.799	3	6
German 6th grade	690	4.861	2.5	6
∅ in math of others in same classroom	690	4.613	3.67	5.19
Gender (1=Female)	690	.543	0	1
Social Class				
EGP I	690	.201	0	1
EGP II	690	.233	0	1
EGP III & IV	690	.235	0	1
EGP V, VI & VII	690	.272	0	1
Other	690	.058	0	1
Language at home				
German	690	.458	0	1
Other language & German	690	.417	0	1
Other language	690	.125	0	1
Financial Situation				
Tense	690	.145	0	1
In between	690	.274	0	1
Relaxed	690	.581	0	1

Table A2: Theoretical parameters regressed on individual background characteristics

	B	*C*	*π*	*p*	*-SD*	*(B+p×-SD)*	*C/p*
Gender (Ref.: boy)							
Girl	-0.043 (0.056)	0.096 (0.071)	-0.008 (0.016)	-0.008 (0.016)	0.058 (0.094)	0.028 (0.091)	0.143 (0.210)
Parental class position (Ref.: EGP I)							
EGP II	0.116 (0.084)	0.005 (0.108)	-0.041^{+} (0.024)	-0.015 (0.024)	-0.053 (0.142)	0.103 (0.137)	-0.030 (0.317)
EGP III & IV	0.191^{*} (0.086)	0.164 (0.109)	-0.044^{+} (0.025)	0.121^{***} (0.025)	0.255^{+} (0.144)	0.390^{**} (0.139)	0.574^{+} (0.322)
EGP V, VI, VII	0.387^{***} (0.088)	0.478^{***} (0.113)	-0.026 (0.026)	0.168^{***} (0.025)	0.461^{**} (0.148)	0.792^{***} (0.143)	1.118^{***} (0.331)
other (unemployed, not in labor force)	0.474^{***} (0.139)	0.626^{***} (0.177)	-0.074^{+} (0.040)	0.126^{**} (0.040)	0.771^{***} (0.233)	1.011^{***} (0.225)	1.507^{**} (0.520)
Language spoken at home (Ref.: German)							
German & other	-0.143^{*} (0.061)	0.155^{*} (0.078)	-0.007 (0.018)	-0.025 (0.018)	0.408^{***} (0.103)	0.108 (0.099)	0.025 (0.230)
Other	-0.058 (0.094)	0.468^{***} (0.120)	0.010 (0.027)	-0.004 (0.027)	0.648^{***} (0.158)	0.306^{*} (0.152)	0.800^{*} (0.352)
City (Ref.: Bern)							
Zurich	-0.102^{+} (0.058)	-0.014 (0.073)	-0.024 (0.017)	-0.021 (0.017)	0.028 (0.097)	-0.118 (0.093)	-0.142 (0.216)
Financial situation (Ref.: relaxed)							
tense	-0.034 (0.086)	0.646^{***} (0.109)	-0.031 (0.025)	0.023 (0.025)	-0.077 (0.144)	-0.063 (0.139)	1.073^{***} (0.322)
in between	0.093 (0.067)	0.445^{***} (0.086)	-0.014 (0.019)	0.003 (0.019)	-0.143 (0.113)	0.000 (0.109)	0.820^{**} (0.252)
N	690	690	690	690	690	690	690
R^2	0.056	0.205	0.017	0.129	0.094	0.100	0.104

Source: DEBIMISS, own calculations; Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Spatial probit estimates: Transition to higher track, controlled for motivation for lower track

	$\boldsymbol{W}$: Neighborhood	$\boldsymbol{W}$: Neighborhood & School	$\boldsymbol{W}$: School
Grade math	1.557*** (0.210)	1.556*** (0.209)	1.634*** (0.224)
Grade German	2.071*** (0.272)	2.095*** (0.273)	2.196*** (0.284)
Mean achievement of others	-1.291*** (0.381)	-1.250** (0.386)	-1.809*** (0.437)
Higher track			
Educ. Motivation $(B_k + p_k \times [-SD])$	-0.136 (0.090)	-0.140 (0.090)	-0.155 (0.093)
Investment Risk (C_k/π_k)	-0.004 (0.042)	-0.004 (0.043)	-0.011 (0.041)
Lagged Terms			
$\boldsymbol{\theta_{B_k+p_k\times(-SD)}}$	-1.119*** (0.311)	-1.024** (0.326)	-0.878*** (0.238)
$\boldsymbol{\theta_{C_k/\pi_k}}$	-0.110 (0.162)	-0.192 (0.168)	-0.259* (0.133)
Lower track			
Educ. Motivation: $(B_l + p_l \times [-SD])$	-0.122 (0.092)	-0.114 (0.092)	-0.104 (0.094)
Spatial Lag (ρ)	-0.007 (0.005)	-0.006 (0.004)	-0.008 (0.009)
AIC	284.15	284.47	272.66
N	690	690	690

Source: DEBIMISS, own calculations; Controlled for parental social class, language spoken at home, sex, financial situation, and city; Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Spatial probit estimates: Transition to higher track, listwise deletion of missing values

	$\boldsymbol{W}$: Neighborhood			$\boldsymbol{W}$: Neighborhood & School			$\boldsymbol{W}$: School		
	Indirect		Direct	Indirect		Direct	Indirect		Direct
Benefits	-0.678***			-0.668***			-0.667***		
(B)	(0.182)			(0.182)			(0.182)		
pr(Success)	3.103***			3.102***			3.099***		
(π)	(0.732)			(0.733)			(0.738)		
Costs	-0.067			-0.065			-0.072		
(C)	(0.123)			(0.123)			(0.125)		
Instrumentality	-1.400*			-1.413*			-1.435*		
(p)	(0.714)			(0.713)			(0.712)		
Status Maintenance	-0.025			-0.024			-0.025		
($-SD$)	(0.084)			(0.084)			(0.085)		
Educ. Motivation		-0.234**	-0.220**		-0.235**	-0.218**		-0.235***	-0.205*
($B + p \times [-SD]$)		(0.080)	(0.082)		(0.080)	(0.082)		(0.080)	(0.085)
Investment Risk		0.005	0.007		0.005	0.006		0.004	0.002
(C/π)		(0.044)	(0.044)		(0.044)	(0.044)		(0.044)	(0.043)
Lagged Terms:									
$\boldsymbol{\theta}_{\boldsymbol{B+p}\times(-\boldsymbol{SD})}$			-0.555†			-0.599*			-0.938***
			(0.291)			(0.290)			(0.261)
$\boldsymbol{\theta}_{\boldsymbol{C/\pi}}$			-0.221			-0.286†			-0.402*
			(0.162)			(0.160)			(0.161)
Spatial Lag (ρ)	0.001	-0.002	-0.001	0.001	-0.000	-0.000	0.006	0.004	-0.007
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.009)	(0.008)	(0.012)
AIC	198.95	229.89	228.01	198.95	229.89	225.85	198.95	229.89	210.60
N	541	541	541	541	541	541	541	541	541

Source: DEBIMISS, own calculations; Controlled for parental social class, language spoken at home, sex, financial situation, city, grade in math and German, and educational achievement of other students at the classroom level; Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Spatial probit estimates: Transition to higher track, missing values with additional random draw

	$\boldsymbol{W}$: Neighborhood			$\boldsymbol{W}$: Neighborhood & School			$\boldsymbol{W}$: School		
	Indirect		Direct	Indirect		Direct	Indirect		Direct
Benefits	-0.404***			-0.404***			-0.404***		
(B)	(0.122)			(0.122)			(0.122)		
pr(Success)	2.191***			2.190***			2.188***		
(π)	(0.445)			(0.445)			(0.444)		
Costs	-0.068			-0.067			-0.067		
(C)	(0.082)			(0.082)			(0.082)		
Instrumentality	-0.545			-0.545			-0.547		
(p)	(0.491)			(0.491)			(0.491)		
Status Maintenance	-0.070			-0.069			-0.069		
($-SD$)	(0.063)			(0.063)			(0.063)		
Educ. Motivation		-0.185**	-0.165**		-0.185**	-0.166**		-0.185**	-0.153*
($B + p \times [-SD]$)		(0.060)	(0.062)		(0.060)	(0.062)		(0.060)	(0.066)
Investment Risk		-0.011	-0.008		-0.011	-0.007		-0.012	-0.015
(C/π)		(0.034)	(0.034)		(0.034)	(0.034)		(0.034)	(0.036)
Lagged Terms:									
$\boldsymbol{\theta_{B+p\times(-SD)}}$			-0.733***			-0.683**			-0.905***
			(0.223)			(0.222)			(0.212)
$\boldsymbol{\theta_{C/\pi}}$			0.096			0.062			0.115
			(0.118)			(0.117)			(0.115)
Spatial Lag (ρ)	-0.000	-0.000	0.001	-0.000	-0.000	0.000	0.002	0.001	-0.005
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.010)
AIC	346.96	375.64	369.08	346.96	375.64	370.14	346.96	375.64	323.92
N	690	690	690	690	690	690	690	690	690

Source: DEBIMISS, own calculations; Controlled for parental social class, language spoken at home, sex, financial situation, city, grade in math and German, and educational achievement of other students at the classroom level; Standard errors in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$